DeepQ Based Heterogeneous Clustering Hybrid Cloud Prediction Using K-Means Algorithm

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Area/Section: Computer Science.
Type of the Paper: Research Paper.
Type of Review: Peer Reviewed as per |C|O|P|E| guidance.
Indexed in: OpenAIRE.
DOI: https://doi.org/10.5281/zenodo.8112164
Google Scholar Citation: IJMTS

How to Cite this Paper:
Sasi Kumar, A., & Aithal, P. S., (2023). DeepQ Based Heterogeneous Clustering Hybrid Cloud Prediction Using K-Means Algorithm. *International Journal of Management, Technology, and Social Sciences (IJMTS), 8*(2), 273-283. DOI: https://doi.org/10.5281/zenodo.8112164

International Journal of Management, Technology, and Social Sciences (IJMTS)
A Refereed International Journal of Srinivas University, India.

CrossRef DOI: https://doi.org/10.47992/IJMTS.2581.6012.0282

Received on: 18/05/2023
Published on: 30/06/2023

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ABSTRACT

Purpose: *The fields of data mining rely heavily on clustering algorithms. Spread information mining systems and fundamentally decentralized batching turned out to be generally utilized over the past 10 years, as they oversee huge and heterogeneous informational indexes that can't be gathered in the center.*

Objectives/Methodology: *For geographic data mining datasets, numerous classification algorithms operate on both local and hierarchical levels. In this paper, we propose a novel method for clustering heterogeneous distributed datasets based on K-Means algorithms (HCA-K-Means). When the algorithm was tested against the BIRCH and DBScan algorithms, it performed better and took less time to run.*

Results/Findings: *In both the partitioning and the organizational groups, there are some flaws. The k-means algorithm allows the number of clusters to be determined in advance for the partitioning class, but in most cases, K is not specified, moreover, hierarchical clustering algorithms have overcome this limit, but still define the stopping conditions that are not straightforward for clustering decomposition. However, the current methods for pruning immaterial groups rely on jumping hyperspheres or even jumping square forms, whose ineffectiveness in the careful search for the nearest neighbor is negated by their lack of snugness.*

Type of Paper: Research Paper

Keywords: Deep Learning, Spatial Dataset, Clustering hybrid cloud prediction, DBScan, K-Means Algorithm,

1. INTRODUCTION :

Over a wide range of fields, data sets are processed and analyzed at an emotional rate, and enormous amounts of knowledge are packed in various locations. In such conditions, data assessment approaches had become fundamental in isolating important data from quickly creating enormous and complex datasets [1]. Experts had additionally made equivalent reevaluations of the consecutively D-M estimations to adjust to immense volumes of data. Although these equivalent variants have a lot of overhead correspondence, they are incompetent and can speed up important estimates [2].
To beat on the over-headed information transmission, Circulated Information Mining (D-DM) systems are recommended which contain two essential headways. Since the data is by and large kept at various areas, the principal objective is to do the information addition method on local area data sets at each knob to yield restricted tests. These results for the locals will be totaled to gather those around the world. Therefore, the level of aggregation of any D-DM assessment has a significant impact on its competence. In this specific circumstance, powerful data mining (DDM) techniques with a sufficient accumulation stage have become important to separate these huge and multidisciplinary sets of information [3].

D-DM is also becoming more and more suitable for large-scale propagated stages like organizations and grids, where data points are frequently distributed geologically and assumed by various associations. Numerous D-DDM Schemes, including the circulated affiliation control system and expressed arrangement, have been developed by various researchers over the past few years or a decade [4].

2. RELATED WORKS :

There are not many fundamental periods of current DDM techniques: 1) restricted experiments with local data on various websites; and 2) the production of prototypes on a national scale by aggregating local results. Because naive direct detection techniques would produce international data models that are unreliable and uncertain, these additional parallel steps are not autonomous [5]. Therefore, DDM would provide an environmental perspective that not only minimizes the impact of local consequences on existing models but also encourages their adoption in order to take advantage of the benefits of collecting information at multiple locations. In a nutshell, effective data leadership is one of the primary determinants of these strategies' success [6]. Also, the data got at various areas utilizing appropriate gear can in any case have various shapes, highlights and accuracy. Traditional relational data mining methods cannot solve any issues with data-driven systems, such as approach precision, dissemination, diversity, and reaction time optimization.

Among the most frequently cited works of literature are: weighted vote, loading, and plurality vote [8]. Multiple methods are used to measure the results in some DDM approaches, which are based on ensemble testing [3]. There are a number of well-suited strategies for operating on distributed networks. For instance, exponential methods for finding temporal associations can be easily translated into the configuration of rationalized frameworks by reducing computational complexity into a hierarchical system and applying it to multi-granular spatial data. The study presents two approaches and methods: purely distributed aggregation-oriented techniques based on a database system or model of execution and parallel techniques that frequently involve sophisticated machines and software to communicate between very expensive parallel systems [9][10].

From the most recent few years, the data is expanding in a gigantic way, this show that current ideas or techniques for data gathering don't figure out very much given the critical issue of information adaptability. As a result, these ideas are brought up for discussion using brand-new approaches with more noble goals. In general, they are based on minor adjustments to fit the particular data at hand [11][12]. The key technique utilized in information extraction is bunching. For knowledge processing, the data object is clustered, and the objects' relationships are also established [13]. The goal is to make the estimation of similarity and difference within a cluster as accurate as possible so that meaningful constructions, processes, and designs can be found in the data [14][15].

3. OBJECTIVES OF THE PAPER :

This paper proposes a K-means algorithm to improve the BP neural network in response to the aforementioned issues. Based on the BP neural network, the algorithm first predicts the values of the missing attributes, greatly enhancing the data's integrity and dependability; subsequently eliminates the abnormal data and, finally, clusters the same data using various perspectives to confirm its relevance to attributes and clustering research. This paper begins by providing a comprehensive overview of the various clustering algorithms, including the classic K-means algorithm and the canopy algorithm.

After utilizing the Canopy algorithm to optimize the initial value of the K-means algorithm, this paper then introduces the parallel Canopy-K-means algorithm by combining the map reduce computing model with the spark cloud computing framework. This paper proposes a parallel adaptive Canopy-K-means algorithm that can be used in the cloud computing framework to adaptively determine the distance threshold parameter T2 based on statistical method because Canopy algorithm needs to introduce a new distance threshold parameter T2 and the parameter needs to be set by human experience. The parallel Canopy-K-means algorithm is optimized by adaptive parameter estimation using the parallelism of the Map-Reduce computing model. This solves the problem that the Canopy process's parameters depend on manual experience selection.

4. HETEROGENOUS CLUSTERING HYBRID CLOUD PREDICTION :

Hierarchy and partitioning are the two main clustering classes. In the literature, numerous generalized methods of current protocols are discussed and several distributed clustering variants have been proposed based on these methodologies, etc. strategies for simultaneous segmentation is subdivided into 2 groups. The first includes techniques that require multiple variations of messages that go around. They need substantial synchronization.

The other sub-category consists of techniques that create and apply local clustering designs to a centralized location in order to produce global models. Notification that editions of the widely used k-means algorithm have to be passed has been suggested. The authors explored the parallelisation of the DBSCAN density-based clustering algorithm., a concurrent message was given passing the BIRCH version of the algorithm. A simultaneous variant of a proposed hierarchical technique, called MPC for Message Forwarding Clustering, was implemented. Most parallel solutions need either several synchronization constraints for process-to-process or a broader perspective of the data, or both.

In both the partitioning and the organizational groups, there are some flaws. The k-means algorithm allows the number of clusters to be determined in advance for the partitioning class, but in most cases K is not specified, moreover, hierarchical clustering algorithms have overcome this limit, but still define the stopping conditions that are not straightforward for clustering decomposition. However, the current methods for pruning immaterial groups rely on jumping hyperspheres or even jumping square forms, whose ineffectiveness in the careful search for the nearest neighbor is negated by their lack of snugness. Spatial requests, expressly nearest to adjoining questions, have been extensively packed in high-layered spaces. While some tests have hypothesized that the infamous "dimensionality devil" at high measurements renders the closest neighbor search using the Euclidean separation metric impractical, others have argued that this is perhaps too pessimistic. To the Mahalanobis separation metric, we expand our separation bouncing technique and note tremendous increases over current lists. In fact, the designers have shown that what defines the execution of the pursuit (in any case for R-tree-like structures) is the inherent dimensionality of the knowledge set, not the dimensionality of the position's space (or the implant's dimensionality).

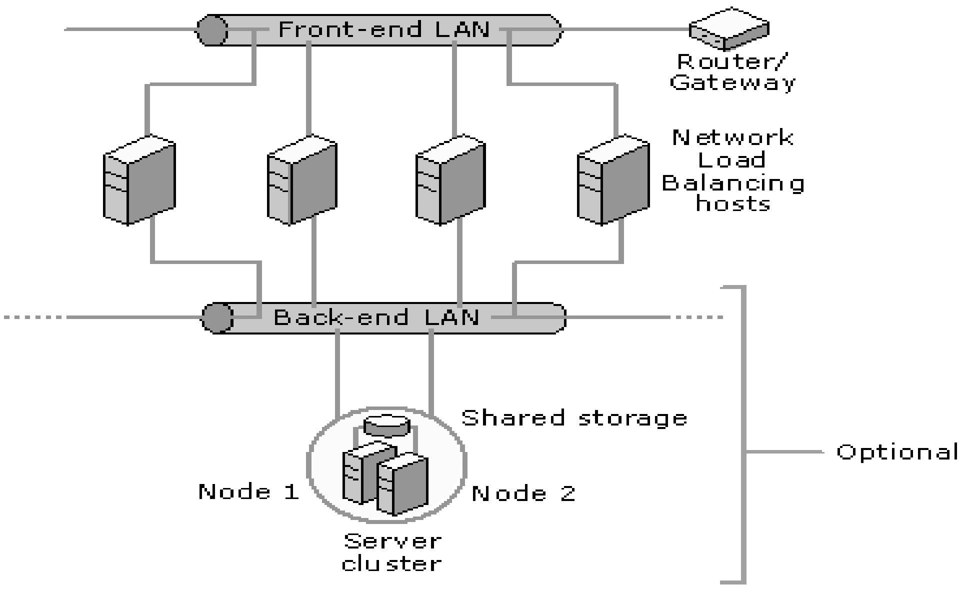


Fig. 1: Heterogenous Computing System – Node and Server [5]

We propose a further group of flexible bound separations based on isolating Voronoi group hyperplane boundaries as a complement to our group-based file. This bond applies to Euclidean and Mahalanobis similarity measurements and enables proficient spatial sifting with relatively low overhead stockpiling pre-handling. Our ordering strategy outflanks a few of the recently proposed lists and is adaptable to the scale and dimensionality of information collections, according to reviews of reliable nearest neighbor set recovery based on actual information collections. Our approach to the ordering of genuine high-dimensional details indexes is depicted on a map. Our focus is on the quest and rehabilitation worldview. The information record is packaged, so that classes can be recovered by diminishing their likelihood of containing parts applicable to the insightful request. We propose a further group of flexible bound separations based on isolating Voronoi group hyperplane boundaries as a complement to our group-based file. This bond applies to Euclidean and Mahalanobis similarity measurements and enables proficient spatial sifting with relatively low overhead stockpiling pre-handling. Our ordering strategy outflanks a few of the recently proposed lists and is adaptable to the scale and dimensionality of information collections, according to reviews of reliable nearest neighbor set recovery based on actual information collections.

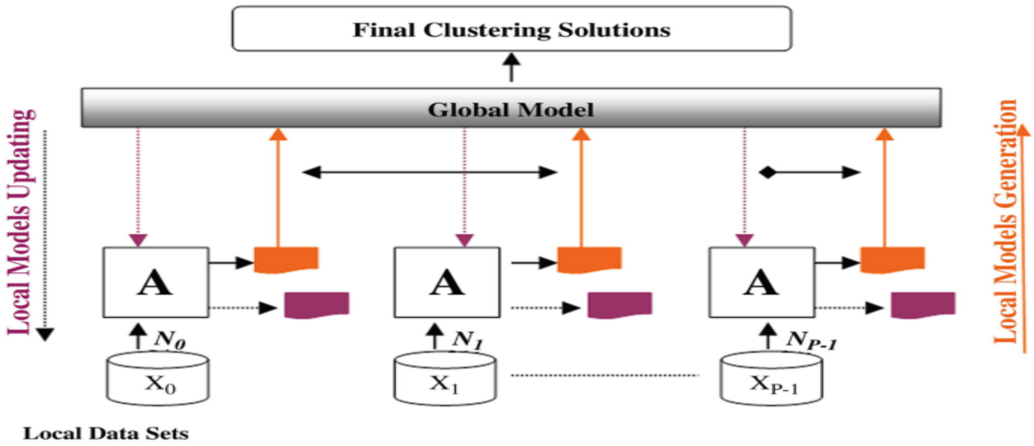


Fig. 2: Clustering System – Hybrid Cloud [7]

5. EXPERIMENTAL SETUP AND SIMULTATIONS :

Our approach to the ordering of genuine high-dimensional details indexes is depicted on a map. Our focus is on the quest and rehabilitation worldview. The information record is packaged, so that classes can be recovered by diminishing their likelihood of containing parts applicable to the insightful request.

Algorithm: DeepQ Heterogeneous Clustering Algorithm

Input: Dp:Partial Dataset, Ci: Number of sub-clusters for Nodei, Dt: degree of tree.
Output: Ct: Total Clusters

Step 1: Apply K-means Algorithm (Dp,Ct);
Step 2: Apply Contour Algorithm for cluster boundary generation (Ci)
Step 3: Nodelinks a group of U & V;
Step 4: Comparison of clusters with other nodes clusters
Step 5: I=Select Leader Node;
    If(m<>1) then
    Transmt (contour m,I);
    Else
    If (level > 0) then
    Level - -;
    Repeat 3,4, and 5 until Level=1
    else
    Return (Ct);

Subsequent to creating nearby tests, each hub contrasts their nearby bunches and the groups of their neighbors. Every one of the hubs called the expert, will be picked utilizing the overlay way to deal with blend nearby bunches to develop bigger gatherings. Any individuals are chosen under different standards, like their authenticity, their figuring limit, and so on. The group consolidation circle will go on before we get to the root hub. The geographic bunches (models) will be inside the root hub. High overheads can be created by speaking with the delegates during the subsequent stage contrasted with insignificant. Therefore, the goal is to ensure precise global efficiency while simultaneously reducing data transmission and processing times. Also, because of subtleties, our strategy lessens cross-over exchange.

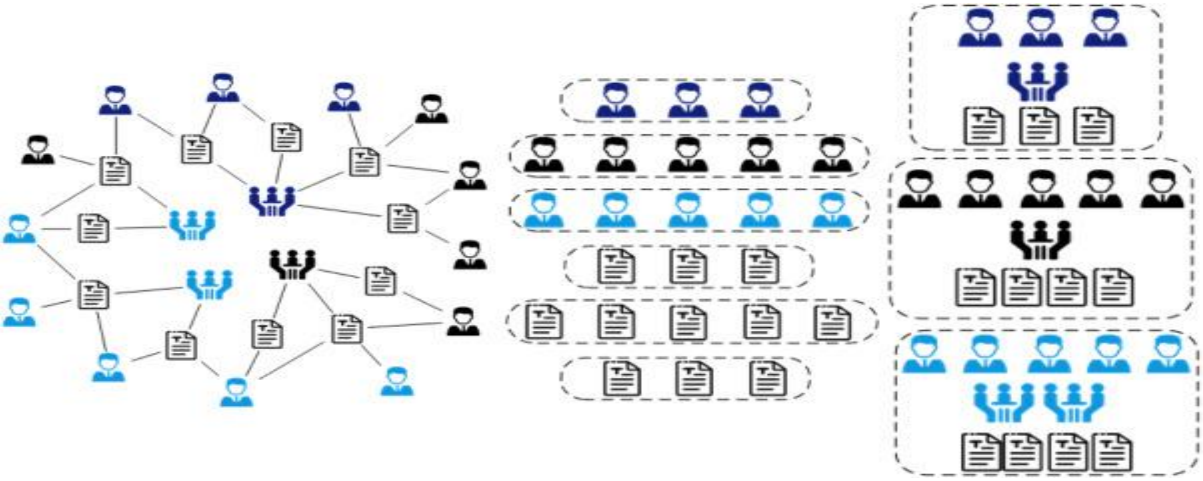


Fig. 3: Classification Cluster node with shapes [11]

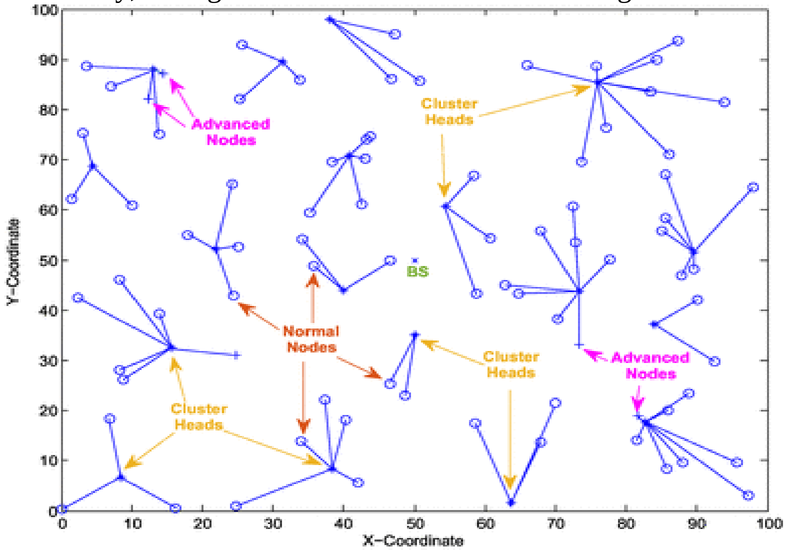
As a result, rather than exchanging all data between nodes (local leaders and nodes) (full clusters), we start by reducing community information. The size of this new data cluster is much smaller than that of the previous one. This activity is led on every one of the nearby hubs. To define the boundaries of the cluster, we made use of the Triangulation-dependent method. It is a potent tool for creating boundaries that are not convex. The methodology can exactly communicate the design of an enormous scope of exceptional point groups and scatterings with O (n log n) of adequate intricacy. Group edges mirror the current dataset, which is a lot more modest than the first assortment of information. The local effects at each framework node should then be the cluster boundaries. These nearby perceptions are shipped off the individuals involving a geography for the plant. The regional figures can be positioned at the arboreal base.

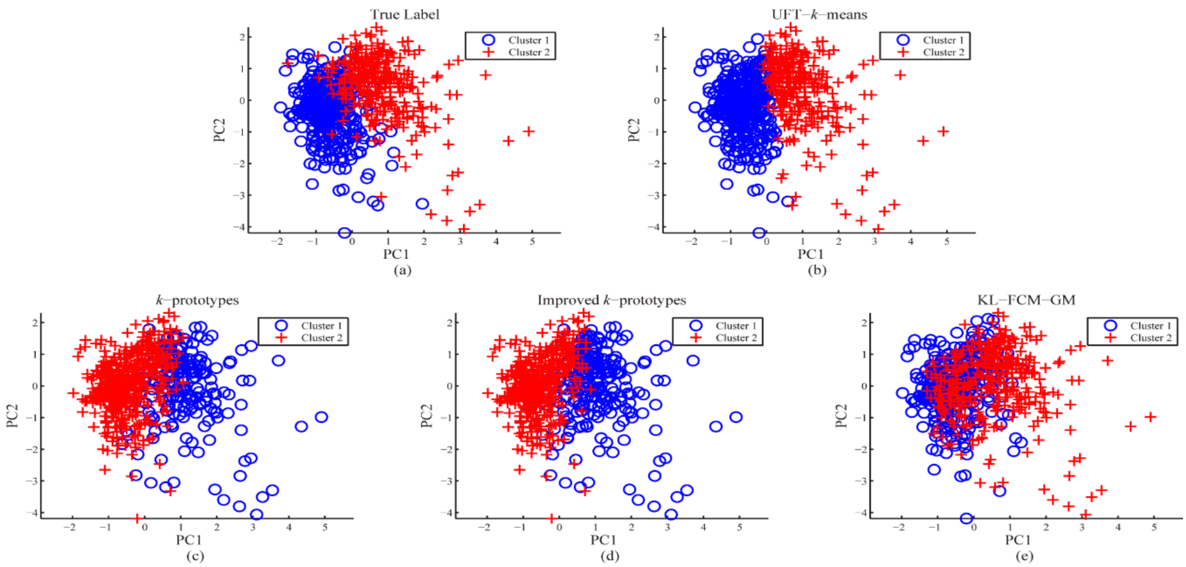
Table 1: Result VMs and Access points using TensorFlow

Datasets	Access Points	Shape – Cluster	Clusters	Precision	Accuracy	Turnaround Time
Dataset_1(VM)	12000	Oval	3	93%	94%	0.32
Dataset_2(RNC)	15000	Circle	2	92%	95%	0.48
Dataset_3(LVM)	21000	Circle	3	93%	94%	0.49

6. RESULTS & DISCUSSION :

Results section, where we'll talk about whether or not our HCA-KMeans Algorithm works. The selection of C(i) greater than the required number of clusters is our main feature. Whenever two groups are consolidated at every calculation stage, the delegate points of the current joined bunch, rather than all places in the new group, are the association of the shapes of the two starting bunches. It helps the organization time without adversely affecting the exactness of the groups created. However, our methodology uses the tree geography and the stack information structures. The algorithm's difficulty is also increased as a result of this. The objective of the reenactment model is to decide the impact of the quantity of gadgets in the framework on the handling time. The example has a million things in it. The ratio of the total amount of equipment to the volume of the cluster's systems is shown in Figure 3. In a distributed network with over 100 nodes, our algorithm clustered 1000,000 points in a matter of seconds. Due to its low difficulty, the algorithm should be able to handle high-dimensional data easily.





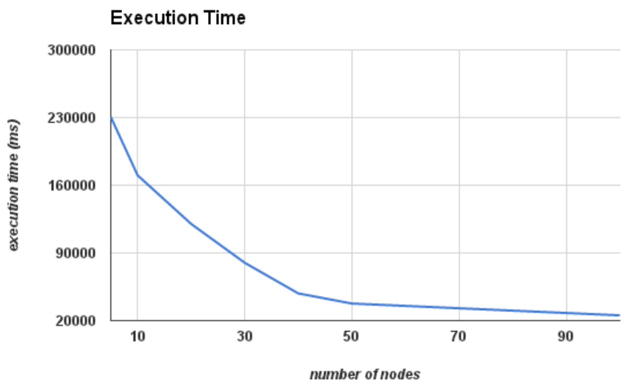


Fig. 4: Simulation results of Accuracy based on Network Latency and Turnaround Time

7. ABCD ANALYSIS OF KMEANS-BASED HETEROGENEOUS CLUSTERING ALGORITHM :

Based on their actions, the artificial bee colony is divided into three groups: employed bee, scout bee, and observer bee The number of employed bees equals the number of onlooker bees at first, and the third type of bee gradually appears. The employed bee gives the observer bee information about the initial honey source that it uses to find a new one. In accordance with the greedy selection mechanism, the observer bee waits in the hive and selects a superior source. However, the corresponding employed bee will become a scout bee if the honey source information has not been updated in a long time. K-means clustering is a type of unsupervised machine learning that tries to group similar observations together. It does this by placing observations in the cluster with the nearest mean after calculating a mean, or centroid, for each random group or cluster.

The centroids are calculated once more after the observations are added to the clusters, and the points are removed from or added to the clusters in accordance. This procedure continues until the clusters are stable—that is, no more observations are added or taken away from the clusters. ABCD analysis can be performed with this straightforward machine learning algorithm [16-22].

7.1 Advantages of Analysis of KMeans – based heterogeneous clustering algorithm Heterogeneous Clustering Hybrid Cloud Prediction:

The advantages of analysis of KMeans – based heterogeneous clustering algorithm Heterogeneous Clustering Hybrid Cloud Prediction.are listed in table 2.

Table 2: Advantages of KMeans-based heterogeneous clustering algorithm Heterogeneous Clustering Hybrid Cloud Prediction

S. No.	Key Indicator	Advantages
1	Formatting Dataset	Datasets can be saved in a variety of formats, including CSV, XLSX, ZIP, TXT, HTML, and PDF.
2	Clustering Dataset	The clustering algorithm works well if all of the clusters are sufficiently dense and well separated by low-density regions. Clusters are defined as continuous regions of high density.
3	Classification	A group alludes to an assortment of information focuses collected together as a result of specific similitudes. The number of centroids required by the dataset will be referred to as the target number, k. You will define this number.
4	Prediction	Each data point is assigned to a group in an iterative manner, and data points gradually become clustered based on features that are similar to one another.
5	F-Score Function	The K-Means clustering algorithm's silhouette score ranges from -1 to 1.
6	Measure	This score indicates how well the data point has been clustered; scores above 0 are considered good, while negative points indicate that your K-means algorithm has placed that data point in the incorrect cluster.

From the above table 2 shows that various key indicators and their advantage based on our results. For this we compute various experimental results of our work.

Table 3: K-Means results - Accuracy index

S. No.	Datasets	Accuracy
1	Dataset_1(VM)	94%
2	Dataset_2(RNC)	95%
3	Dataset_3(LVM)	94%

Table 4: K-Means results - Prediction values

S. No.	Datasets	Precision
1	Dataset_1(VM)	93%
2	Dataset_2(RNC)	92%
3	Dataset_3(LVM)	93%

Table 5: K-Means results - Turnaround Time

S. No.	Datasets	Advantages
1	Dataset_1(VM)	0.32
2	Dataset_2(RNC)	0.48
3	Dataset_3(LVM)	0.49

The multiple iterations are done for the dataset of VM, RNC,LVM which is selected from UCI repository. TensorFlow simulator is used to simulate the network and deep belief network is generated. From the results average accuracy is achieved as 95% and we achieved lesser turnaround time.

7.2 Benefits of Analysis of KMeans – based heterogeneous clustering algorithm Heterogeneous Clustering Hybrid Cloud Prediction:

The benefits of analysis of KMeans – based heterogeneous clustering algorithm Heterogeneous Clustering Hybrid Cloud Prediction.are listed in table 6.

Table 6: The benefits of analysis of KMeans – based heterogeneous clustering algorithm Heterogeneous Clustering Hybrid Cloud Prediction.

S. No.	Key Indicator	Benefits
1	Data Classification	Classifies the data based on support vector features. So we can get normalized values
2	Preprocessing	It can be done by using data cleaning. So we reduce redundant data
3	Feature Extraction	Extracted features from connected components and set factor as zero
4	Measurements	Final results obtained from various testing iterations

From the above table each key indicators are identified and benefits are recorded. Process iteration can be done for selecting features and results are analyzed

7.3 Constraints of Analysis of KMeans – based heterogeneous clustering algorithm Heterogeneous Clustering Hybrid Cloud Prediction:

The constraints of analysis of KMeans – based heterogeneous clustering algorithm Heterogeneous Clustering Hybrid Cloud Prediction.are listed in table 7.

Table 7: The constraints of analysis of KMeans – based heterogeneous clustering algorithm Heterogeneous Clustering Hybrid Cloud Prediction.

S. No.	Key Indicators	Constraints
1	Features	Selecting features are multiple iterations and measurements
2	Classifier	Redundant dataset classifications are tedious
3	Support Vector	Choosing multiple iterations results are time consuming to get prediction results
4	Machine Learning	Huge processing and mathematical representations are required

From the above table 7, various key indicators are selected and measured the constraints. Each results are recorded to found the accuracy.

7.4 Disadvantages of Analysis of KMeans – based heterogeneous clustering algorithm Heterogeneous Clustering Hybrid Cloud Prediction:

The disadvantages of analysis of KMeans – based heterogeneous clustering algorithm Heterogeneous Clustering Hybrid Cloud Prediction.are listed in table 8.

Table 8: The disadvantages of analysis of KMeans – based heterogeneous clustering algorithm Heterogeneous Clustering Hybrid Cloud Prediction.

S. No.	Key Indicators	Disadvantages
1	Clustering	Clustering can be done using selected key features
2	Aggregation	It is normalized vector process so taking huge time consuming
3	Parallelism	Considered turn around and exclusion time overall results pulldown
4	Accuracy	Accuracy is recorded bur execution time increased

From this case various features are selected and mentioned disadvantages. Based on various iterative results our proposed approach gives better result.

8. CONCLUSION :

For the purpose of controlling the spatial distribution of large datasets, we proposed a KMeans-based heterogeneous clustering algorithm. By increasing parallelism and decreasing interchanges, this method exploits the distributed stage's planning speed, primarily by increasing the scale of the system's knowledge exchange between hubs. After performing a bunching calculation in each center, the results of the surrounding areas are combined to form the global groups in neighborhood models. In order to make them small enough to be traded across the network, neighborhood designers are referred to. The scope of the assessment is expanding. We should anticipate performing tests on particular neighborhood equations and examining the potential outcomes of applying the methods to a variety of large and annexed datasets.

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